# Analysis and Generation of Pavement Distress Images Using Fractals

JEFFREY LEBLANC, MICHAEL A. GENNERT, NORMAN WITTELS, AND DAVID GOSSELIN

Pavement surface distress information, collected by automated surface distress evaluation equipment, can be used in pavement management systems to plan the timely maintenance of roads and highways. Images acquired at highway speeds contain such large amounts of data that practical digital data storage systems are easily overwhelmed. Fractals have been investigated as a means of compressing pavement distress images, after the distress has already been detected in pavement images by other methods. These stored, compressed images could be analyzed by computers later to characterize the severity and extent of the distress or they could be used to reconstruct the distress image for evaluation by a pavement maintenance engineer. The advantage of treating a pavement crack as a fractal curve is that it can be represented by only a few numbers. The basic fractal characterizations, including the fractal dimension, of some forms of pavement distress have been measured and are presented; a midpoint displacement algorithm that is useful for compressing and simulating distress images is described; basic methods for applying fractal models to distress image compression are discussed; a method for simulating pavement surface distress images is presented; and the use of fractal techniques to generate standard images for testing automated surface distress evaluation systems is proposed.

Planning of cost-effective maintenance of roads and highways is a complicated process requiring collection and evaluation of large amounts of data. The need for timely and accurate information becomes acute as transportation agencies increasingly introduce pavement management systems (PMSs) (*1–3*). A key input to a PMS is a current system-wide assessment of the status of pavements, including the location, severity, and extent of pavement distress. Collecting distress data manually is tedious, inaccurate, and expensive. Research and development work on automated pavement surface distress evaluation systems that can acquire and evaluate images of distressed pavements at highway speeds is in progress; a recent survey of progress has been compiled by Cable (*4*).

The data rates of real time image acquisition systems are large, on the order of 50 to 100 Mbytes per second for a system specified to inspect a 4-m-wide lane at highway speed while detecting 1.6-mm-wide cracks (*5*). Two approaches have been developed for handling this flood of data. In the first approach, the data are analyzed in real time and only summaries of distress severity and extent are recorded by the survey vehicle. Although this approach solves the data rate problem, the raw data have been discarded. Therefore, it is difficult for a pavement maintenance engineer to perform many useful functions, such as evaluating the causes of distress and comparing the results of annual surveys to study pavement wear. In the second approach, commercial video cameras and recording equipment, which are capable of recording up to several hours of video images on tape cassettes or video disks, acquire images for evaluation at a later time. This approach retains raw data, but commercial video equipment, typically with 4 Mbytes per second of bandwidth, is fundamentally incapable of meeting the performance specification.

One solution to the data rate problem would be a special-purpose, high-resolution image acquisition system coupled with data compression to allow recording raw image data at highway speeds using commercial equipment. The pavement distress images could be stored and reconstructed at a later time for direct study by humans or for image processing by automated machine vision systems. Tests conducted during the course of this research indicated that standard data compression techniques, such as the Ziv-Lempel algorithm (*6*), only reduce the data rates by factors of about 2, not the factors of 100 to 1,000 that are required. Statistically based compression algorithms designed for television use allow greater compression (*7,8*). However, they are designed to reconstruct images that are judged by human observers as being comparable to the original images; there is no assurance that the reconstructed images will produce the same results when evaluated by a machine vision system.

A search was undertaken to find techniques for compressing pavement surface distress images such that the reconstructed images are equivalent. Images are defined to be equivalent if they meet two criteria. First, humans must evaluate that they depict the same extent and severity of distress. Second, machine vision image processing must determine that the images depict the same distress, including extent and severity. This requirement does not mean that the results are the same when human and computer evaluations are compared; it means that human-to-human and computer-to-computer evaluations are consistent. The comparison of human-to-computer results is a central problem of automated pavement distress evaluation and is beyond the scope of this paper.

An investigation of the use of fractals, an extension of mathematical set theory, in the analysis and generation of pavement distress images is described. Fractals allow complicated images to be constructed by mathematical algorithms with only a few adjustable parameters (*9*). If the proper algorithm can be found, images of surface distress can be reduced to a few parameters that can be stored and used for later reconstruction of an equivalent pavement distress image.

The scope of this paper is limited in several respects. Of the many forms of pavement distress, only models of linear

J. LeBlanc, M. A. Gennert, and D. Gosselin, Department of Computer Science; N. Wittels, Department of Civil Engineering; Worcester Polytechnic Institute, Worcester, Mass. 01609.

distress features—simple longitudinal, transverse, and diagonal cracks—are discussed. More complicated forms of distress, such as alligator cracking, have been left for future work. Also, only the problem of compressing and reconstructing images of the distressed portions of pavement images is considered. The assumption has been made that other image processing algorithms have previously distinguished distressed from sound pavement. However, that is a difficult problem (*10*). A long-term research goal is to develop a model-based pavement segmentation algorithm that is based on this work. Finally, complete image reconstruction accuracy is not the objective of the work; it is only necessary to retain sufficient information to allow accurate assessment of severity and extent of pavement and surface distress by both humans and computer.

## FRACTALS

A fractal is a self-similar mathematical function defined as a set of points whose fractional Hausdorff-Besicovitch dimension $D$ is strictly larger than its topological dimension (*11*). Because $D$ can be a fraction (noninteger), it is called the "fractal dimension" and the function is called a "fractal." The term "self-similar" means that the function looks the same on a large scale as it does on a small scale (*12*). This requirement describes a pavement distress image: even if a section of a crack is magnified, it still looks like a crack. Curves that are self-similar, such as cracks, can be represented as fractals. The properties of fractals will be discussed first and then fractal analysis will be applied to images of pavement surface distress.

### Fractal Dimension

A coastline is an example of a self-similar curve that can be described by a fractal (*11*). Suppose one were to measure the length of the coastline using a ruler with a length of 100 km; the result might be 200 km. Now, perform the measurement with a ruler length of 10 km. The result might now be 260 km because the smaller ruler better fits into the nooks and crannies of the coastline. The smaller the ruler, the longer the coastline's measured length. This is shown schematically in Figure 1. Unlike a straight line, a fractal's measured length depends on the ruler's length. This dependence is described by $D$, the curve's fractal dimension. Although there are other measures that are sometimes useful for describing and characterizing fractals, the fractal dimension is a key parameter of fractals used in pavement distress applications.

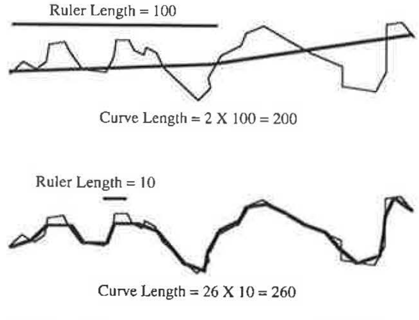


**FIGURE 1 Curve's measured length depends on ruler's length.**

In order to contrast fractal dimension with Euclidean dimension, consider using a ruler of length $K$ to measure the length of a straight line of length $L$ by placing the ruler end-to-end $N$ times:

$$N = \frac{L}{K} \tag{1}$$

When the line is not straight but convoluted, the number of rulers $N$ needed to fit the curve grows even faster. This dependence can be modeled by changing the exponent.

$$N = \left(\frac{L}{K}\right)^D \tag{2}$$

where $D$ is the fractal dimension of the curve. For a straight line, $D = 1$. The dimension $D$ must be less than $D = 2$, for that would correspond to a curve so convoluted that in traveling between two points it has nonzero area (contradicting the Euclidean notion of a line). For any nonstraight curve, such as the coastline, the fractional dimension is between $D = 1$ and $D = 2$, with larger numbers corresponding to more erratic curves.

A detailed discussion of fractal dimension is provided by Falconer (*13*). For application to pavement distress problems, the primary requirements are means for measuring the fractal dimension of cracks in pavement images and means for generating pavement distress images given the fractal dimension.

### Measuring Fractal Dimensions of Pavement Surface Distress

There are several methods available for measuring the fractal dimension of a data set (*9*). Most methods used in image processing are designed to measure the complexity of two-dimensional data, such as the randomness of a leopard's spots, the variation in brush stroke texture in a painting, or the puffiness of clouds. However, pavement distress consists predominantly of linear features—cracks. A modification of the caliper method, which is useful for measuring the fractal dimensions of linear structures (*14*), has been found to provide the most consistent results when applied to pavement distress images.

The first step in measuring the fractal dimension is to segment the distress from a pavement image. Figure 2 shows, as an example, a distressed region of a portland cement concrete (PCC) pavement. In Figure 3, the distress has been segmented. That is, the gray levels in the image have been altered so that distressed regions are pure black and nondistressed regions are pure white. Segmentation is a major problem in automated pavement distress (*15*); the segmentation of this particular image has been described by Wittels et al. (*10*).

The morphology—the shape of the distress—is of interest; therefore, the segmented image is skeletonized (*16*). Skeletonization reduces the width to the smallest possible picture

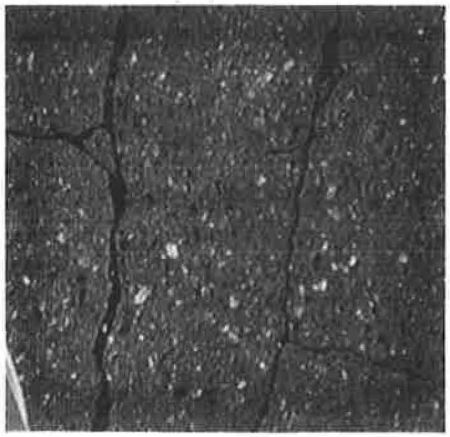

FIGURE 2 Image of distressed PCC pavement.

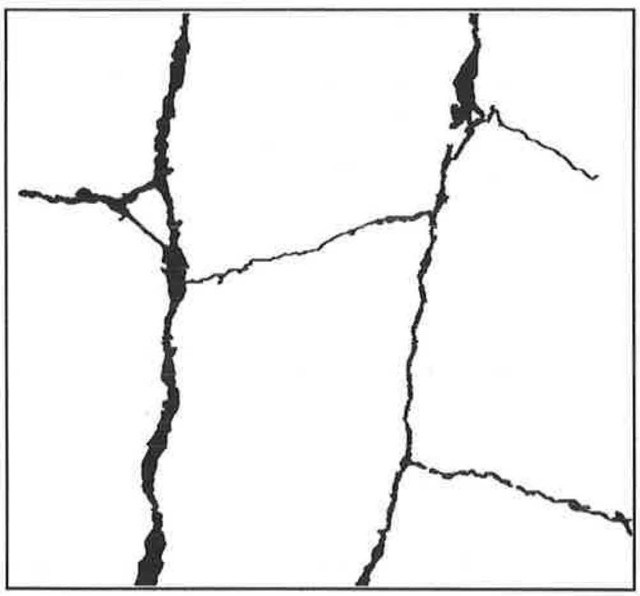

FIGURE 3 Segmented image of the distress in Figure 2.

element, a pixel. Figure 4a shows a transverse crack from Figure 3; Figure 4b shows the same crack after skeletonization.

Next, the measured length $M$ (in pixels) of the skeletonized crack is determined using a variety of ruler lengths $K$ (in pixels). As described by Smith et al. (*14*), a log-log plot of $M$ as a function of $K$ is drawn (Figure 5), and the slope $S$ is computed. The fractal dimension $D$ is then

$$D = 1 - S \quad (3)$$

The crack shown in Figure 4 has fractal dimension $D = 1.08$. Ideally, the log-log plot should be a straight line; in practice, it never is. For small values of $K$, the fact that the digital image is discrete (pixels are larger than points) means that the left end of the curve is generally too flat; self-similarity breaks down at the pixel level. For large values of $K$, the fact that the length is not an integral number of ruler lengths causes quantization errors. The selection of which points to use in calculating the slope has been made arbitrarily; ruler lengths between 10 and 100 pixels have provided the most repeatable results. In order to automate fractal dimension measurements, a more rigorous slope measurement method will have to be developed.

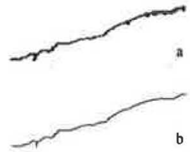


FIGURE 4 (*a*) A transverse crack from Figure 3, and (*b*) a skeletonized transverse crack.

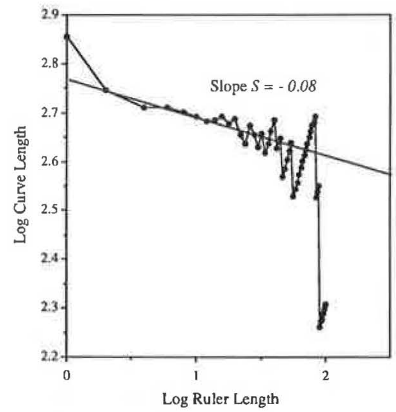


FIGURE 5 Log-log plot of curve length versus ruler length, from Figure 4b.

From analyzing digitized images of surface distress in both PCC and asphalt cement (AC) pavements, all of the measured cracks were found to have fractal dimensions in the range $D = 1.10 \pm 0.05$. Linear features, such as joints in PCC pavements, have fractal dimensions below this range and curves with fractal dimensions above this range are too wiggly to be realistic cracks (Figure 6). No theoretical reason has been identified to explain why cracks should have fractal dimensions within the given range. Also, because of the difficulty in reliably segmenting distress, measurements have only been made on a small number of distress images (approximately 20). These data are not enough to support a claim that the measured fractal dimension range is universal, nor even enough to report reliable statistical measures, such as the standard deviation of the fractal dimension.

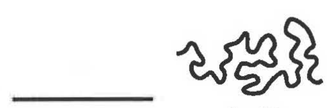


FIGURE 6 Curves with fractal dimensions outside the range $D = 1.10 \pm 0.05$.

**Using Fractals to Simulate Pavement Surface Distress**

One goal of this research was to find methods for generating realistic pavement images. The two tests of realism are that the images appear to correctly represent distressed pavements when viewed by humans and that the images behave the same as naturally acquired pavement images when processed by the algorithms in an automated pavement surface distress evaluation system. The search for such methods has been described by Gosselin and LeBlanc (*17*), so only a summary is presented.

Fractals are generated by iterative applications of functions, called generators, to Euclidean objects. When simulating pavement distress, a straight line is dissected into smaller line segments by the generator. The resulting line segments are themselves dissected by applying the same generator, and so forth, until the resulting dissections are undetectable (smaller than a pixel). Successful simulation of pavement distress requires selecting both the form and parameters of the generator. It is important to point out that there exists no general theory for designing or selecting optimal fractal generators so the usual method, and the one that was employed, is to search for the generator that produces curves that most look like the data; the judgment is artistic, not scientific.

The fractal-generating function can be either deterministic or stochastic. A deterministic generator is applied identically at each iteration. An example of a deterministic fractal is the Koch snowflake. Its generator trisects a line segment (Figure 7a) and replaces the central segment with two segments of equal length (Figure 7b). After applying the generator $G$ times, the resulting curve has $3^G$ segments; Figure 7c shows the case of $G = 3$. In principle, the curve is a fractal only in the limit as $G$ approaches infinity; in practice $G$ need only be larger than the logarithm, base two, of the image size in pixels. For example, if the digital image is $2^8 = 512$ pixels wide, $G$ need only be greater than or equal to 9.

Although the fractal in Figure 7 is interesting, it does not resemble a pavement crack for two reasons. First, it is too crooked. The fractal dimension produced by a generator such as the Koch snowflake is (*18*)

$$D = \frac{\log (N)}{\log 1/R} \tag{4}$$

where $N$ is the number of segments into which the line is dissected and $R$ is the ratio of the new line segment length to the original line length. For the Koch snowflake, $N = 4$ and $R = ⅓$ so $D = 1.262 \ldots$, which is outside the measured range of pavement distress fractal dimensions. The second problem with the fractal in Figure 7 is that it is too regular to realistically depict pavement distress. This example indicates that the required fractal generator should allow control on the fractal dimension and should produce more irregular fractals.

Irregular fractals can be produced by stochastic generators, in which an element of randomness is introduced into the line segment dissection process. In contrast to a deterministic generator, at each iteration all line segments are not replaced in exactly the same way. Instead, the lengths and orientations of the new segments are allowed to vary in a random fashion. The generator that has been found to be most useful for pavement distress is stochastic. It is one of a class of midpoint displacement generators (*11*).

Consider a generator that bisects a line segment by displacing the midpoint to produce two new line segments. In its deterministic form, the midpoint is always displaced by the same amount; Figure 8a shows a generator in which the midpoint is displaced in an orthogonal direction by one-quarter of the original line length. For convenience, the line length has been chosen to be $l = 1$ with no loss of generality. In the stochastic form, both the magnitude, $r$, and the direction, $\theta$, of the displacement are selected randomly so that the midpoint is displaced uniformly within a closed circle of radius $p$. Therefore the displacement angle, $\theta$, is uniformly distributed within the complete circle $0 \leq \theta \leq 2\pi$ and the probability density of any angle $\theta$ is

$$P_\theta(\theta) = \frac{1}{2\pi} \tag{5}$$

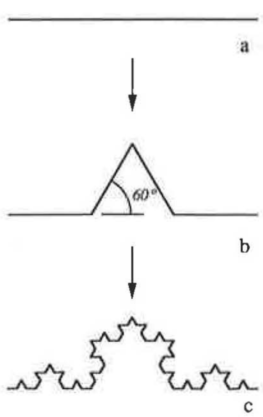


**FIGURE 7** **(*a*) Line segment used for generating a fractal, (*b*) Koch snowflake generator, and (*c*) curve after three iterations of the generator.**

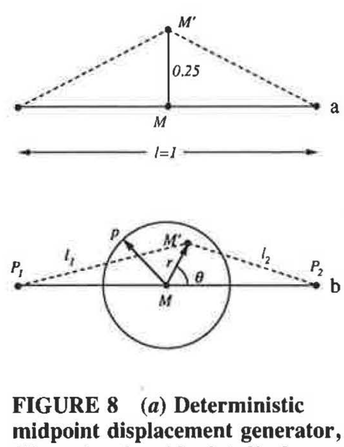


**FIGURE 8** **(*a*) Deterministic midpoint displacement generator, and (*b*) stochastic midpoint displacement generator.**

In order to obtain a uniform distribution of midpoints, the probability density of any displacement magnitude $r$ must be

$$P_r(r) = \frac{2r}{p^2} \tag{6}$$

The fractal dimension of a curve generated using this stochastic generator is given by Equation 4, where $N = 2$ and $R = E\{l_1\}$ is the average or expected value of $l_1$, the length of the line $P_1M'$ connecting an endpoint to the displaced midpoint in Figure 8b. Because the two line segments $P_1M'$ and $P_2M'$ obey the same statistics, the expected values of their lengths are equal to each other and that value is

$$E\{l_1\} = E\{l_2\} = \int_0^p \int_0^{2\pi} P_r(r) P_\theta(\theta)\ l_1(r,\theta) dr d\theta \tag{7}$$

in which $P_\theta$ and $P_r$ are given by Equation 5 and 6, respectively, and $l_1$ can be computed from the geometry of Figure 8b.

$$l_1(r,\theta) = (0.25 + r^2 + r \cos \theta)^{1/2} \tag{8}$$

The fractal dimension $D$ is plotted as a function of the parameter $p$ in Figure 9. Small values of $p$ produce almost straight curves. Values of $p$ that match the measured fractal dimensions of pavement distress lie in the range $0.25\ 0 \leq p \leq 0.425$ and values greater than 0.5 produce curves too crooked to be considered realistic pavement images. The upper limit on $p$ is about 0.85, above which the fractal dimension exceeds 2 (the curve is no longer a line but rather becomes area-filling). Two examples of digital images of fractal curves produced using this stochastic midpoint displacement algorithm are shown in Figure 10.

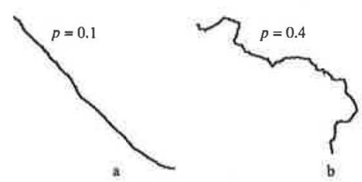


**FIGURE 10 Fractals produced by a stochastic midpoint displacement generator.**

## Crack Width

A fractal curve generated as described has no width; that is, it is a curve composed of line segments that are one dimensional. For graphical purposes, a constant width of one or two pixels was used when producing the figures. However, a real pavement crack has nonzero, nonconstant width. The goal in this work was not to characterize crack width; it was to produce more realistic images of pavement surface distress. Thus, a simple algorithm was implemented that assigns a width to each line segment along the crack.

The width at one end of the crack is specified as an input to the process. The algorithm then assigns a width to each of the straight line segments that form the fractal. Points are constructed at both segment ends a constant perpendicular distance from the segment, defining a box of a constant width around the segment. The box width is randomly generated except that its width is constrained to vary by no more than one pixel from the width of the preceding segment. That is, a segment's width is the same as that of the previous segment, plus or minus one pixel. Additionally, upper and lower limits (minimum and maximum widths, respectively) are used as inputs to the process. In order to ensure that the curve is continuous, the box end points are connected end to end by pie-shaped polygons. Finally, the line segments are replaced by the boxes and polygons to form the final crack image. As an example, Figure 11 shows the crack of Figure 10b with width information added.

There is no theoretical basis for this crack width algorithm; it was selected because the resulting images appear to be realistic in that it produces smooth width variations reminiscent of real pavement distress. Future work should be undertaken to develop an algorithm based on theoretical models of pavement cracking or on measured crack widths in pavement distress images.

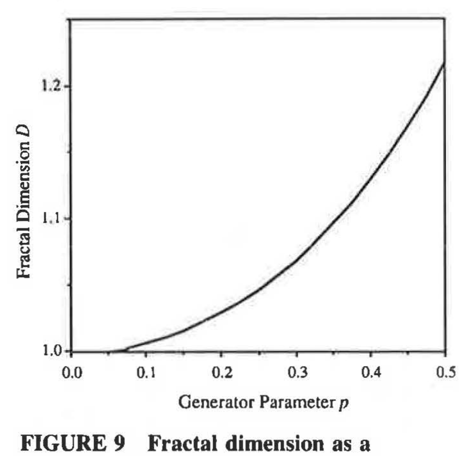


**FIGURE 9 Fractal dimension as a function of the generator parameter.**

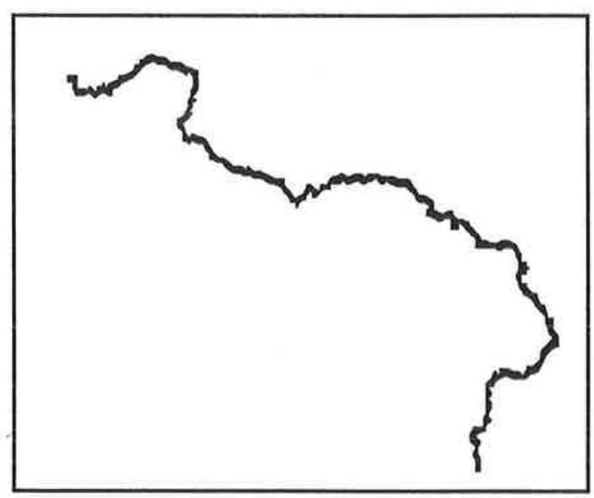

**FIGURE 11 A fractal curve with algorithmically produced width.**

### Generating Pavement Images

The remaining difference between fractal crack images, such as Figure 11, and a digital image of real pavement distress, such as Figure 2, lies in their gray levels. Pavements are not uniform; the lightness or darkness of any pixel depends on the materials, geometry of distress, and lighting conditions (*15,19*). Using the segmented distress image as a mask and computer models to compute the correct gray levels, it is possible to alter pavement images to simulate changes in lighting or paving materials (*10*). Using this method, the image of Figure 2 was altered in two steps. First, the segmented distress image, Figure 3, was used as a mask to remove the distress. Then, the computed distress image, Figure 11, was used as a mask to produce an image of a distressed pavement. The resulting pavement image is shown in Figure 12.

In order to produce the distress portion of this image, only 13 parameters were used: the crack end point locations (two horizontal and two vertical pixel numbers), the fractal dimension, the beginning crack width, the minimum and maximum crack widths (two numbers), the assumed crack depth, the average pavement surface reflectivity, two illumination angles, and the ratio of directed and ambient illumination. This represents about 1/500th of the data in the original image. If another distress image were produced using the same parameters, it would be distinguishable from Figure 12 but should be judged by both humans and automated pavement analysis systems as having the same distress type, severity, and extent.

## DISCUSSION AND CONCLUSIONS

Attempts were made to assess the overall reconstruction accuracy of the fractal methods presented. Although methods exist for comparing the accuracy of image reconstruction (*20*) by pixel-by-pixel comparison of image gray levels, there are no generally acceptable methods for comparing image equivalency as defined earlier. One indicator of overall accuracy is a comparison between the fractal dimension used to generate a curve and the fractal dimension measured from the same curve. Consider the two fractal curves in Figure 10. Table 1 presents the values of $p$ used in producing these digital images, the fractal dimensions $D$ calculated from $p$ using equation 7, and the values of $D$ measured from the digital images using the method described earlier. These results are typical. Additionally, Table 1 indicates a measurement on Figure 7c. The discrepancies in the results are moderate and show the general quality of the results; the major discrepancy is caused by the difficulties in determining the slope of log-log plots such as Figure 5.

**FIGURE 12 Simulated image of a distressed PCC pavement.**

A major appeal of fractals is their ability to significantly reduce the amount of data required to store distress images. The data reduction estimates presented earlier compared the data content of the distress (the data of interest for automated pavement surface distress evaluation) with the data content of the complete image (the raw data). In fact, most of the information in a pavement image is from the aggregate; that is why the image processing task is so daunting—comparable to searching for needles in haystacks. Should it be deemed necessary to characterize and store information sufficient to reconstruct the aggregate image as well, the data reduction will not be as large. It is also worth noting that initial measurements suggest that fractal methods might also be useful for characterizing aggregate.

In light of the limited overall accuracy described earlier, it is useful to question whether fractal methods can be expected to meet the equivalency requirement posed earlier. The human part of the equivalency test can only be established by showing original and reconstructed images to pavement maintenance engineers and comparing the distress scores they assign to the images. No attempt has yet been made to perform this comparison but it should be done in the future. The computer part of the equivalency test is easier to address. Wittels and El-Korchi (*19*) established that computer modeling is capable of interpreting and generating image gray levels that are correct to within the noise levels of typical image acquisition systems. Therefore, image processing algorithms should find the individual pixel level gray levels to be indistinguishable, which would cause them to assign equivalent distress severity and distress scores. There is need for further study to verify this equivalence.

### Uses of Fractal Models

The primary goal of this research was to find methods suitable for compressing pavement surface distress images. The general suitability of fractal methods has been established, but that is a long way from a working image compression system. Future work will be required to incorporate this technology into an operational automated pavement surface distress evaluation system.

TABLE 1 COMPARISON BETWEEN THEORETICAL AND MEASURED FRACTAL DIMENSION

| Image | Generator $p$ | Generator $D$ | Measured $D$ |
|---|---|---|---|
| Figure 10a | 0.1 | 1.006 | 1.06 |
| Figure 10b | 0.4 | 1.129 | 1.11 |
| Figure 7c | | 1.262 | 1.26 |

As mentioned previously, segmenting distress from pavement images is a major technical challenge (*15*) because the distress is often masked by aggregate in the images. A promising use for fractal techniques is in model-based segmentation. In this approach, potential distress sites are located and assigned probabilities that they are in fact distress. The known characteristics of distress are then used to iteratively adjust the probabilities of adjacent sites. Segmentation based on models of image gray levels have been proposed (*10*); it could be augmented by fractal methods. If adjacent sites are part of the same distress, the cracks they form when they are linked have fractal dimensions that can be computed and compared with the known range of acceptable values; the site probabilities are adjusted according to the fractal dimension. Model-based segmentation has the possibility of significantly improving the quality of distress image segmentation.

A third possible use for fractal analysis is in generating pavement test images. The question of which image processing algorithms are optimal for automated pavement evaluation is still open and subject to current research. Therefore, it is neither obvious which suite of these images will adequately test performance of an operational system nor which should be used for testing during algorithm development. Synthesized test images have the advantage over naturally acquired pavement images in that their geometric and photometric characteristics are known. The analogy to the eye chart used by ophthalmologists has been presented (*10*); more can be learned about a patient's vision by showing him/her standard images of known size and contrast than by displaying random street scenes. By using the methods presented, it is possible to generate test images that are suitable for both developing and testing pavement evaluation systems.

### Direction of Future Work

There are many directions in which the reported work could lead. Many have been mentioned so they are only summarized below. This list represents an educated guess about the directions in which major advances lie or in which better confirmation of what is known is required.

- The equivalence between original and reconstructed pavement distress images for both human pavement maintenance engineers and image processing computers needs to be more firmly established.
- This work would be more firmly established if theoretical explanations were available to calculate or explain why cracks have fractal dimensions within the observed range. Statistical fracture models (*21*) may lead to such an understanding.
- Use the methods presented to generate test images for developing and testing pavement evaluation systems.
- Explore fractal methods for characterizing, compressing, and reconstructing aggregate in pavement images.
- The work in this paper has only considered one form of distress—isolated cracks. Additional efforts will be required to extend the methods to handle other types of distress that are important in pavement maintenance, such as alligator cracking, raveling, D cracking, potholes, and patches.

It has been found that fractal methods are useful in the analysis, compression, and generation of images of simple forms of pavement surface distress. A method that is useful for measuring the fractal dimension of cracks was presented and values measured from pavement distress images were reported. A midpoint displacement algorithm was found to be effective in generating pavement distress images that are equivalent to acquired images for purposes of evaluating pavement surface distress. These synthesized images have use in designing and testing image processing systems and algorithms for automated pavement distress evaluation.

## ACKNOWLEDGMENTS

The help and encouragement of others who contributed to this work are gratefully acknowledged. In particular, A. Bealand and S. Annecharico assisted in obtaining the pavement distress data; T. El-Korchi and M. O. Ward provided valuable technical critique of the research. The reviewers of the first draft of this paper are thanked for their helpful comments. The data collection phase of this work was supported by the Research Development Council of the Worcester Polytechnic Institute.

## REFERENCES

1. R. Haas and W. R. Hudson. *Pavement Management Systems.* McGraw-Hill, New York, 1978.
2. S. G. Ritchie. Expert Systems in Pavement Management. *Transportation Research A*, 21A, 1987, pp. 145–152.
3. D. S. Turner, J. V. Walters, T. C. Glover, and E. R. Mansfield. An Asphalt Pavement Rating System Based on Highway Maintenance Engineers' Experience. In *Transportation Research Record 951*, TRB, National Research Council, Washington, D.C., 1986, pp. 9–16.
4. J. Cable, ed. *Proc., Automated Pavement Distress Data Collection Equipment Seminar*, Iowa State University, Ames, 12–15 June 1990.
5. T. El-Korchi, M. A. Gennert, M. O. Ward and N. Wittels. An Engineering Approach to Automated Pavement Surface Distress Evaluation. *Proc., Automated Pavement Distress Data Collection Equipment Seminar*, Iowa State University, Ames, 12–15 June 1990, pp. 165–174.
6. J. Ziv and A. Lempel. A Universal Algorithm for Sequential Data Compression. IEEE *Transactions on Information Theory*, IT-23, 1977, pp. 337–343.
7. A. N. Netravali and B. G. Haskell. *Digital Pictures.* Plenum Press, New York, 1988.
8. W. F. Schreiber. *Fundamentals of Electronic Imaging Systems.* Springer, Berlin, 1986.
9. M. Barnsley. *Fractals Everywhere.* Academic Press, Boston, Mass., 1988.
10. N. Wittels, T. El-Korchi, M. A. Gennert, and M. O. Ward. Images for Testing Automated Pavement Surface Distress Evaluation Systems. *Proc., Automated Pavement Distress Data Collection Equipment Seminar*, Iowa State University, Ames, 12–15 June 1990, pp. 153–164.
11. B. Mandelbrot. *The Fractal Geometry of Nature.* W. H. Freeman, New York, 1982.
12. J. Gleick. *Chaos: Making a New Science.* Viking Press, New York, 1987.
13. K. J. Falconer. *The Geometry of Fractal Sets.* Cambridge University Press, London, 1985.
14. T. G. Smith, Jr., W. B. Marks, G. D. Lange, W. H. Sheriff, and E. A. Neale. A Fractal Analysis of Cell Images. *Journal of Neuroscience Methods*, Vol. 27, 1989, pp. 173–180.

15. T. El-Korchi and N. Wittels. Visual Appearance of Surface Distress in PCC Pavements: I Crack Luminance. In *Transportation Research Record 1260*, TRB, National Research Council, Washington, D.C., 1990, pp. 74–83.
16. R. J. Shalkoff. *Digital Image Processing and Computer Vision*. Wiley, New York, 1989.
17. D. Gosselin and J. LeBlanc. *Generation and Analysis of Fractal Pavement Surface Distress Images*. Technical Report WPI-CS-TR-90-11. Department of Computer Science, Worcester Polytechnic Institute, Worcester, Mass., 1990.
18. H. O. Peitgen and D. Saupe, eds. *The Science of Fractal Images*. Springer-Verlag, New York, 1988.
19. N. Wittels and T. El-Korchi. Visual Appearance of Surface Distress in PCC Pavements: II Crack Modeling. In *Transportation Research Record 1260*, TRB, National Research Council, Washington, D.C., 1990, pp. 84–90.
20. B. Bian. *Accurate Simulation of Scene Luminances*. Ph.D. dissertation, Worcester Polytechnic Institute, Worcester, Mass., 1990.
21. H. J. Herrmann and S. Roux, eds., *Statistical Models for the Fracture of Disordered Media*. North-Holland, Amsterdam, Netherlands, 1990.

*Publication of this paper sponsored by Committee on Pavement Monitoring, Evaluation, and Data Storage.*